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Energy Technologies Area
September, 2017

Comparison of typical year and multiyear building simulations using a 55-year actual weather data set from China

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Abstract:

Weather has significant impacts on the thermal environment and energy use in buildings. Thus, accurate weather data are crucial for building performance evaluations. Traditionally, typical year data inputs are used to represent long-term weather data. However, there is no guarantee that a single year represents the changing climate well. In this study, the long-term representation of a typical year was assessed by comparing it to a 55-year actual weather data set. To investigate the weather impact on building energy use, 559 simulation runs of a prototype office building were performed for 10 large cities covering all climate zones in China. The analysis results demonstrated that the weather data varied significantly from year to year. Hence, a typical year cannot reflect the variation range of weather fluctuations. Typical year simulations overestimated or underestimated the energy use and peak load in many cases. With the increase in computational power of personal computers, it is feasible and essential to adopt multiyear simulations for full assessments of long-term building performance, as this will improve decision-making by allowing for the full consideration of variations in building energy use.

Keywords:

Typical year, Multiyear simulation, Actual weather data, Building simulation, Energy use, Peak load

1. Introduction

The global building sector consumes nearly one-third of the world's total energy [1]. The outdoor climatic conditions together with the building envelope, equipment used, and occupants in the building determine the total building energy consumption and the indoor thermal environment. Weather is an important factor when sizing and selecting HVAC (heating, ventilation, and air-conditioning) systems and lighting systems with daylight controls. Additionally, the energy production of weather-based renewable energy systems, such as solar energy systems and wind power systems, are influenced directly by the variability in climate. Because buildings are rather complicated, nonlinear, and dynamic systems, computer modeling and simulations are widely recognized as an efficient means of predicting the future performance of a building [2], 3]. All the simulation tools used worldwide require reliable weather data inputs to drive the simulations accurately. However, different weather data sets in simulation tools can result in large discrepancies among the results [4]. In short, accurate and compatible weather data are fundamental and indispensable to the building professions.

Generally, a one-year weather sequence, known as a typical meteorological year, is used as the weather input to building simulation tools. The weather file usually contains 8760 hourly records of meteorological elements and is derived from a multiyear database to represent the long-term climatic conditions. In the last few decades, several data sets have been developed by different research institutions, which use various data structures and selection methods. A typical year could be an actual calendar year, such the Test Reference Year (TRY) [5], or a synthetic year consisting of 12 typical meteorological months (TMM) selected from historic weather data, such as the Typical Meteorological Year (TMY) [6] and the weather year for energy calculation (WYEC) [7], as well as the updated versions of them including TMY2 [8], TMY3 [9], and WYEC2 [10]. Given the fact that hourly weather data are not always available for some cities or sites, a synthetically generated meteorological year (SMY) can be a practical option [11]. For this purpose, hourly weather data are produced in accordance with the statistical summary data available, such as monthly or daily data; hence, SMY data can follow the sequence of real monthly or daily weather fluctuations well [12]. In addition, the synthesized data can represent the variations and uncertainties of climate to some extent [13].

Many efforts have been made to generate typical meteorological years in multitudinous locations globally, including Nigeria [14], 15], Greece [16], Cyprus [17], Syria [18], 19], Malaysia [20], Spain [21], Thailand [22], 23], Saudi Arabia [24], South Korea [25], and Turkey [26]. In China, several typical year data sets have been published in recent years. These data sets are diverse in terms of the data sources, recording periods, and site quantities as well as the selection methods used. A typical meteorological database for 57 Chinese locations, generally called the (Chinese Typical Year Weather) CTYW database, was developed by Zhang et al. [27], 28] in 2004. Because of a lack of observed solar radiation data, solar radiation was estimated by using other meteorological elements. In 2005, the Climatic Data Center of the China Meteorological Administration along with Tsinghua University developed a meteorological data set for 270 Chinese cities [29]. This data set, known as the Chinese Standard Weather Database (CSWD), has been used extensively in China and adopted into many simulation tools such as DeST [30] and EnergyPlus [31]. Yang et al. [32] investigated typical years for 60 cities in the five major climatic zones of China. In the paper by Chan et al. [33], weather data for a 25-year period (1979–2003) in Hong Kong were used to derive TMY data. Many other researchers have developed typical meteorological years for a variety of sites in China [34]–36].

As can be seen in the state-of-the-art research, plenty of typical year data files have been developed worldwide, but appropriate weather data inputs must be used for building energy simulations. Crawley

[37] indicated that single year, TRY-type weather data cannot represent typical long-term weather; instead, a synthetic year such as TMY2 or WYEC2 was recommended. Among the methods for deriving TMY files, there is no agreement either on the number of weather parameters to use or on the weighting of the weather parameters [38]. Some authors even claim that the generation of typical year weather data is not very sensitive to the weighting of different weather variables [39]. Studies have shown that climate change has significant impacts on building energy use [40], 41], and thus, it needs to be incorporated in urban infrastructure planning [42]; because of the climate change taking place globally and its vital role in energy use, the record period for TMY selection should accordingly contain recent meteorological data and be reasonably long enough to reflect the climatic trend well [43]. Two sets of weather data files were formed based on different periods to assess their impact on the accuracy of building energy analyses [44]. This study found that the weather file developed with far older data underestimated the electricity consumption by up to 14.5%.

Although there is no doubt that typical year files can simplify the prediction process and reduce the computational work, some shortcomings are rooted in the selection method used for obtaining weather data. First, whichever method is used, the typical year is derived in compliance with the same criteria for the weather variables involved and the weightings. However, the criteria used for a typical year depend largely on the particular types or systems of buildings. For example, work on a solar-based building should place a high weight on solar radiation during the development of a typical year, whereas wind data should be the dominant parameter in the typical year selection process for a building that mainly uses natural ventilation. In other words, the typical meteorological year somehow assumes “an average building [2]” without taking into account the various sensitive variables of different building types and systems. To compare the performance of each TRY, 17 TRYs were applied to several typical energy systems [16]. The simulation results showed that the most optimal type of TRY differs from system to system. Second, a typical year does not necessarily represent the average value of the historic long-term climate and cannot reflect the variation and uncertainty inherent in the actual weather data. Some studies have shown that the building energy use predicted by a typical year followed the long-term mean quite well [34], 45], 46], whereas the conclusion from other research was that the representativeness of a typical year’s results could vary significantly in the considered locations [38]. Moreover, climate is such a complex and changeable phenomenon in which much variety can be found from year to year. As a result, the variation in annual building energy use calculated by using actual weather data can be significant. The energy use of office buildings in eight United States (U.S.) locations was simulated by using a 30-year actual weather data set [37]. It was concluded that annual energy consumption varied by as much as -11.0% to 7.0%. Predictions of peak cooling loads of fully air-conditioned office buildings in Hong Kong were found to differ by up to 14% [47]. Wang et al. [48] indicated that the impact of year-to-year weather fluctuations on energy use ranged from -4% to 6% in four cities in the U.S. The energy use during a typical year is just a single value, and thus, it inevitably fails to represent the variation range caused by actual weather fluctuations. Lastly, because they represent typical rather than extreme conditions, typical years are not suitable for designing systems that can accommodate worst-case conditions [8]. Given the limitations of a typical year, some authors have created an Extreme Meteorological Year (XMY) [49] or Untypical Meteorological Year (UMY) [50] to capture building performance under extreme conditions.

Considering the above factors, it is time to rethink the utilization of a typical meteorological year in building energy predictions and comparative energy efficiency studies. Because it is possible to run hundreds of simulations in mere minutes nowadays thanks to the rapid development in computational power, direct simulations with multiyear actual weather databases should be considered when assessing building performance. There are many benefits to using multiyear simulations instead of a single typical year. As buildings can have a long life cycle (greater than 50 years), the assessment and prediction of long-term building performance is very important. Simulations with multiyear actual weather data allow for comprehensive understanding of building performance in a long-term weather series from a life-cycle perspective. Such assessments provide the variation range in building energy use due to the changeable climate rather than single value data. Furthermore, building designers and operators or policymakers can evaluate the likelihood of any weather conditions and adopt appropriate response strategies based on the simulation results. Any year required for a specific design aim, such as an extremely hot year or a specific calendar year, can be chosen from a multiyear database easily. A few studies have investigated the advantages of multiyear building simulations over typical year simulations. Hui et al. [51] presented a pilot study in Hong Kong regarding long-term building energy performance using multiyear weather data. Large-scale simulations were conducted by Hong et al. [52] to analyze the sensitivity of building energy use and peak demand in relation to yearly variations in weather with multidecade Actual Meteorological Year (AMY) weather data from 17 climate zones in the U.S. Pernigotto et al. [38] investigated the annual variability in energy results by using multiyear simulations for five locations in Italy and analyzed its effects on the building envelope energy ratings.

Despite numerous studies on the generation of typical years for Chinese locations, only a few have focused on the variation in weather data as well as its impact on building use and peak load throughout the climate zones of China. Additionally, the necessity of adopting a multiyear simulation method has not been deeply evaluated. The aims of this study were to compare a typical year weather file with the actual long-term weather data of major cities in China, not only from a statistical perspective of the weather parameters but also from an energy use perspective, and to answer the following questions:

1) Is the typical year weather file a good representation of the long-term weather for all climate zones in China?
2) Can building energy consumption and peak load predicted by the TMY match the long-term means well?
3) How much variation occurs in building energy use because of climate change?
4) Does the extent of variation differ from city to city?
5) What is the possible risk of using TMY weather data in building energy predictions?

2. Methodology

2.1. Overview

To address the research questions listed at the end of Section 1, the following five main steps were conducted during the analysis:

1) Develop a typical year data file for China;
2) Prepare a multiyear weather database for simulation needs;
3) Analyze the variation in weather data and a representative typical year file;
4) Set up a prototype building model using building simulation tools; and
5) Compare the energy use and peak demand predicted by the typical and actual weather years.

Many typical years have been developed by different groups in China. One of the most widely adopted typical year files is the CSWD, which was published by the Climatic Data Center of the China Meteorological Administration and Tsinghua University in 2005. Both the simulation tools DeST and EnergyPlus use this database as their weather input for Chinese locations. In this study, a typical year in CSWD was used to analyze the differences between typical year simulations and multiyear simulations.

For the second step, the raw historical weather data for 10 major cities in the five climate zones of China were collected from the China Meteorological Administration. The record period ranged from 1960 to 2014, except for the city of Xi'an, for which the data ended in 2013 because the station was moved. Data processing was conducted to derive the multiyear weather database. The processing of raw data involved unifying the format of the source data, filling in the missing data gaps, excluding outliers, and interpolating the weather data from six-hour intervals to generate the hourly data. The processing method was the same as that used to produce the CSWD, and further details can be found in the literature [29]; this earlier study proved that the generated weather data were in agreement with the observed hourly data. The weather data were observed manually and recorded every six hours throughout a day (02:00, 08:00, 14:00, and 20:00) before 2004 in China. After the upgrade to automatic observations in 2004, hourly recorded data became available for most of the weather stations. The processing procedures for these data were similar to those used for the typical year generation so as to ensure that the database had the same format as the typical year file, i.e., so that it could be used with the building simulation tools.

Next, representative typical year weather data for the long-term climate were investigated. The dry-bulb temperature, absolute humidity, and total global horizontal solar radiation were selected as the key parameters for the comparison. Heating degree days (HDD) and cooling degree days (CDD), which are indices that represent not only the extent but also the duration of cold and hot weather, were also compared.

Commercial buildings, especially office buildings, are one of the most common building types in China. Therefore, we did the analysis on a typical office building. A prototype office building was set up in DeST to simulate the building performance. The configuration of the model was compliant with the building energy efficiency standard of China [53]. A total of 56 simulation runs (55 actual weather years and 1 typical year) were carried out in each city, except Xi'an, which only had 55 runs. Therefore, 559 simulation runs were conducted to consider the variety in weather data. The total energy consumption and peak demand data were used to provide a clear picture of how the typical year results differed from those of actual years.

2.2. Weather data

China is a vast country with various climatic conditions. To implement appropriate strategies and standards according to the different climate characteristics, the country has been classified into five major climate zones: the severe cold zone (SCZ), the cold zone (CZ), the hot summer and cold winter zone (HSCWZ), the hot summer and warm winter zone (HSWWZ), and the temperate zone (TZ). This climate classification framework is based principally on the average temperature of the coldest and hottest months. In our study, 10 major cities covering these climate zones were investigated. The geographic location of each city is shown in Fig. 1. These 10 cities were distributed relatively uniformly across China. Detailed information for each site is listed in Table 1. A long-term weather series for the 10 cities consisting of 55 years worth of data from 1960 to 2014 was compiled. The Xi'an station, however, only had a 54-year record because the site was moved to another location far from the urban area and thus its meteorological record ended in 2013.

Fig. 1. Geographic location of the 10 major cities studied

Table 1. Summary of the multiyear weather database for the 10 cities in China

Number	Province	City	Climate zone	Latitude	Longitude	Elevation (m)	Period	Total years
1	Xinjiang	Urumqi	SCZ	43°47’	87°39’	935	1960–2014	55
2	Heilongjiang	Harbin	SCZ	45°56’	126°34’	118.3	1960–2014	55
3	Beijing	Beijing	CZ	39°48’	116°28’	31.3	1960–2014	55
4	Tibet	Lhasa	CZ	29°40’	91°08’	3648.9	1960–2014	55
5	Shanxi	Xi’an	CZ	34°18’	108°56’	397.5	1960–2013	54
6	Shanghai	Shanghai	HSCWZ	31°24’	121°27’	5.5	1960–2014	55
7	Zhejiang	Hangzhou	HSCWZ	30°14’	120°10’	41.7	1960–2014	55
8	Guangdong	Guangzhou	HSWWZ	23°13’	113°29’	70.7	1960–2014	55
9	Hainan	Haikou	HSWWZ	20°00’	110°15’	63.5	1960–2014	55
10	Yunnan	Kunming	TZ	25°00’	102°39’	1888.1	1960–2014	55

It is vital to prepare a multiyear weather database file correctly to fulfill the simulation requirements. In general, attention should be paid to missing data, spikes, and data formatting [54]. In China, the meteorological record interval is generally 6 h rather than 1 h before 2004. Because hourly data are required as weather inputs in DeST, the 6 h interval weather data needed to be interpolated to hourly data. The methods to do so were the same as those used for generating the CSWD data files [29]. More information about the data processing methods can be found in the literature [29]. The observed weather data consisted of major meteorological parameters such as the dry-bulb temperature, relative humidity, wind speed and direction, ground temperature, atmosphere pressure, and solar radiation. Other required parameters that were not observed, such as enthalpy and dew point temperature, were calculated from the observed parameters.

2.3. Prototype building

A prototype building model was set up in DeST. The building model was established based on a real medium-sized office building with seven stories and a total air-conditioning floor area of 5550 m^2. Each floor is 3.9 m high. The layout of the building is shown in Fig. 2. It is a representation of a typical concrete-slab-type office building in China. The shape coefficient of the building was 0.176, and the window–wall ratio was 0.4 for all four orientations. The occupant density was set to 10 m^2/person, and the lighting and equipment densities were 9 W/m^2 and 15 W/m^2, respectively. The work hours were modeled as 07:00–18:00 from Monday to Friday. The building envelope properties were configured according to the Chinese national standard for public buildings [53], which was issued in 2015. Because of the diversity of climatic conditions in each climate zone, the emphasis on building envelope design was obviously different for the different zones. For example, Harbin is a rather cold city and the average outdoor air temperature of the coldest month is lower than -10 ℃. In such a city, the heating loss through the building envelope in winter is the major consideration in the building design. The envelope characteristics should fully meet the requirements of insulation in winter, whereas the cooling demand is of relatively less importance. In contrast, in Haikou, where the average temperature of the hottest month is 25–29 ℃ and that of coldest month is higher than 10 ℃, the cooling demand is generally the dominant issue of concern. As a result, the building envelope performance of each city varied significantly from each other. The specific envelope characteristics of the 10 cities are shown in Table 2.

The HVAC system was also developed based on the design code mentioned above. Briefly, the operating hours of the HVAC system were the same as the working hours. The set point temperature was 26 ℃ in summer and 20 ℃ in winter. Space cooling was provided by water-cooled centrifugal chillers. The system COP (coefficient of performance) was 2.5. The heating system was determined by the climate zone. A coal-fired boiler with an efficiency of 60% was used in the SCZ and CZ, whereas a natural gas-fired boiler with an efficiency of 75% was used in the other climate zones. A two-pipe fan coil system was used in all the climate zones for space cooling.

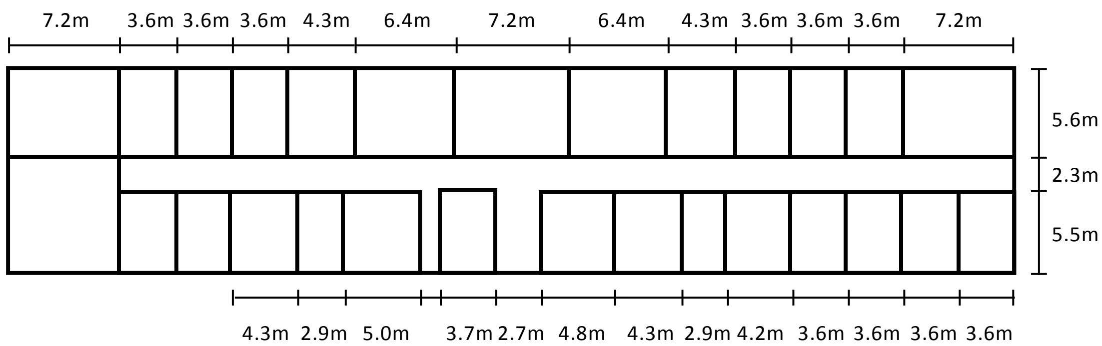

Fig. 2. Plan view of the prototype building model

Table 2. Building envelope characteristics in the 10 cities in China

No.	City	Climate zone	U-value (W/m^2K)			Window
			Roof	Wall	Window	SHGC

1	Harbin	SCZ	0.28	0.38	2.2	N/A
2	Urumqi	SCZ	0.35	0.43	2.3	N/A
3	Beijing	CZ	0.45	0.5	2.4	0.48
4	Lhasa	CZ	0.45	0.5	2.4	0.48
5	Xi’an	CZ	0.45	0.5	2.4	0.48
6	Shanghai	HSCWZ	0.5	0.8	2.6	0.44
7	Hangzhou	HSCWZ	0.5	0.8	2.6	0.44
8	Guangzhou	HSWWZ	0.8	1.5	3	0.35
9	Haikou	HSWWZ	0.8	1.5	3	0.35
10	Kunming	TZ	0.8	1.5	3	0.4

3. Results

3.1. Variation in weather data and representation of a typical year

3.1.1. Statistical analysis

The statistical results for the annual average dry-bulb temperature of the 10 cities from 1960 to 2014 are listed in Table 3. The maximum, minimum, mean, and standard deviation of the yearly average temperature were calculated. To understand the variation inherent in the local climate quantitatively, the maximum and minimum range were compared to the long-term average. The results showed that the variation range for the annual average dry-bulb temperature varied from 1.9 ℃ to 4.5 ℃ in the different cities. Harbin had the most variation with a range of 4.5 ℃ (-50.1% to 51.1% of the means), whereas the annual average dry-bulb temperature of Guangzhou varied the least with a range of 1.9 ℃ (-3.8% to 5.0% of the means). The variation in weather data was more significant in the heating-dominant cities such as Harbin, Urumqi, and Lhasa. However, it should be noted that the low average value may have magnified the percentage of the variation range. The large variation rate was due not only to the large change range, but also to the low multiyear means.

Table 4 lists the statistical results for the annual average global horizontal solar radiation. The variation range varied from 3.1 MJ/m^2 (Shanghai) to 8.5 MJ/m^2 (Lhasa) for the 10 sites over the 55-year record period.

Table 3. Statistics for the annual average dry-bulb temperature in the 10 cities from 1960 to 2014

	Max	Min	Mean	Range	STD	Max change of the mean	Min change of the mean	CSWD	Variation (CSWD-Mean)	Variation change of the mean
Unit			℃			%	%	℃	℃	%
Harbin	6.7	2.2	4.4	4.5	1.0	51.1	-50.1	4.1	-0.3	-7.0
Urumqi	9.0	5.1	7.4	3.9	0.9	22.0	-30.9	7.1	-0.2	-3.2
Beijing	14.1	10.6	12.4	3.6	0.9	13.8	-15.1	12.6	0.2	1.8
Lhasa	10.3	6.3	8.2	4.0	0.9	25.7	-23.4	8.3	0.1	1.0
Xi’an	16.0	12.8	14.0	3.2	0.9	14.0	-8.7	14.1	0.1	0.9
Shanghai	18.4	15.1	16.3	3.3	0.8	12.6	-7.8	16.7	0.4	2.2
Hangzhou	18.7	15.7	16.7	2.9	0.7	11.5	-6.0	17.0	0.3	1.6

Guangzhou	23.2	21.3	22.1	1.9	0.5	5.0	-3.8	22.2	0.1	0.5
Haikou	25.4	23.2	24.2	2.2	0.6	5.3	-4.0	24.3	0.2	0.8
Kunming	16.7	13.7	15.2	3.0	0.8	9.9	-10.1	15.5	0.3	1.8

Table 4. Statistics for the annual average global horizontal solar radiation in the 10 cities from 1960 to 2014

	Max	Min	Mean	Range	STD	Max change of the mean	Min change of the mean	CSWD	Variation (CSWD-Mean)	Variation change of the mean
Unit			MJ/m^2			%	%	MJ/m^2	MJ/m^2	%
Harbin	16.0	11.6	12.8	4.4	0.8	24.7	-9.8	12.6	-0.3	-2.1
Urumqi	16.5	12.0	14.2	4.5	0.9	16.4	-15.3	13.5	-0.7	-4.8
Beijing	17.0	12.4	14.3	4.6	1.2	19.1	-12.9	13.8	-0.5	-3.2
Lhasa	23.5	15.0	20.2	8.5	1.9	16.0	-26.1	20.0	-0.2	-1.0
Xi’an	14.2	9.5	12.2	4.7	1.1	16.5	-22.0	11.7	-0.5	-4.2
Shanghai	13.7	10.6	12.8	3.1	0.6	6.9	-17.7	12.5	-0.3	-2.2
Hangzhou	14.9	9.0	11.7	5.9	1.1	27.4	-23.1	11.9	0.2	1.4
Guangzhou	14.7	9.1	11.7	5.6	1.0	25.6	-22.5	11.2	-0.5	-4.2
Haikou	16.7	9.9	13.7	6.8	1.3	21.5	-27.9	13.3	-0.5	-3.3
Kunming	18.0	12.9	15.0	5.1	1.0	20.1	-14.0	15.1	0.1	0.7

Notes: The ninth and tenth columns display the absolute and relative discrepancies, respectively, between the typical year and the multiyear average values.

To analyze the representative typical year file of the weather variables, the average temperature and global horizontal solar radiation of the CSWD typical year were determined, and the data are listed in Table 3 and Table 4, respectively. From the statistical results, it can be concluded that the typical year can approximate the multiyear means well from the perspective of annual weather parameters. The differences ranged from -7.0% to 2.2% for the annual average temperature and from -4.8% to 1.4% for the annual average global horizontal solar radiation across the climate zones in China.

In summary, the yearly weather data varied significantly in all the climate zones. The cold climate cities varied much more in terms of temperature than the warm climate cities did. The typical year was a good representation of the long-term means regarding the weather variables. However, in view of the typical year being a single year, the variation in the long-term yearly climate could not be considered fully.

3.1.2. Monthly weather profiles

The monthly weather profiles of temperature and solar radiation are shown in Fig. 3 and Fig. 4, respectively, for the purpose of detailed comparisons. It can be seen that the typical year was a better representation of the monthly average temperature than the monthly average global horizontal solar radiation. The monthly average temperature of the typical year was quite similar to both the mean and median values of the multiyear actual weather data series in most of the cities. Nevertheless, the monthly global horizontal solar radiation of the typical year differed significantly from the long-term means and medians from month to month, especially in Xi’an and Shanghai. In general, it cannot be easily concluded that the typical year represented the long-term weather well from the perspective of monthly weather.

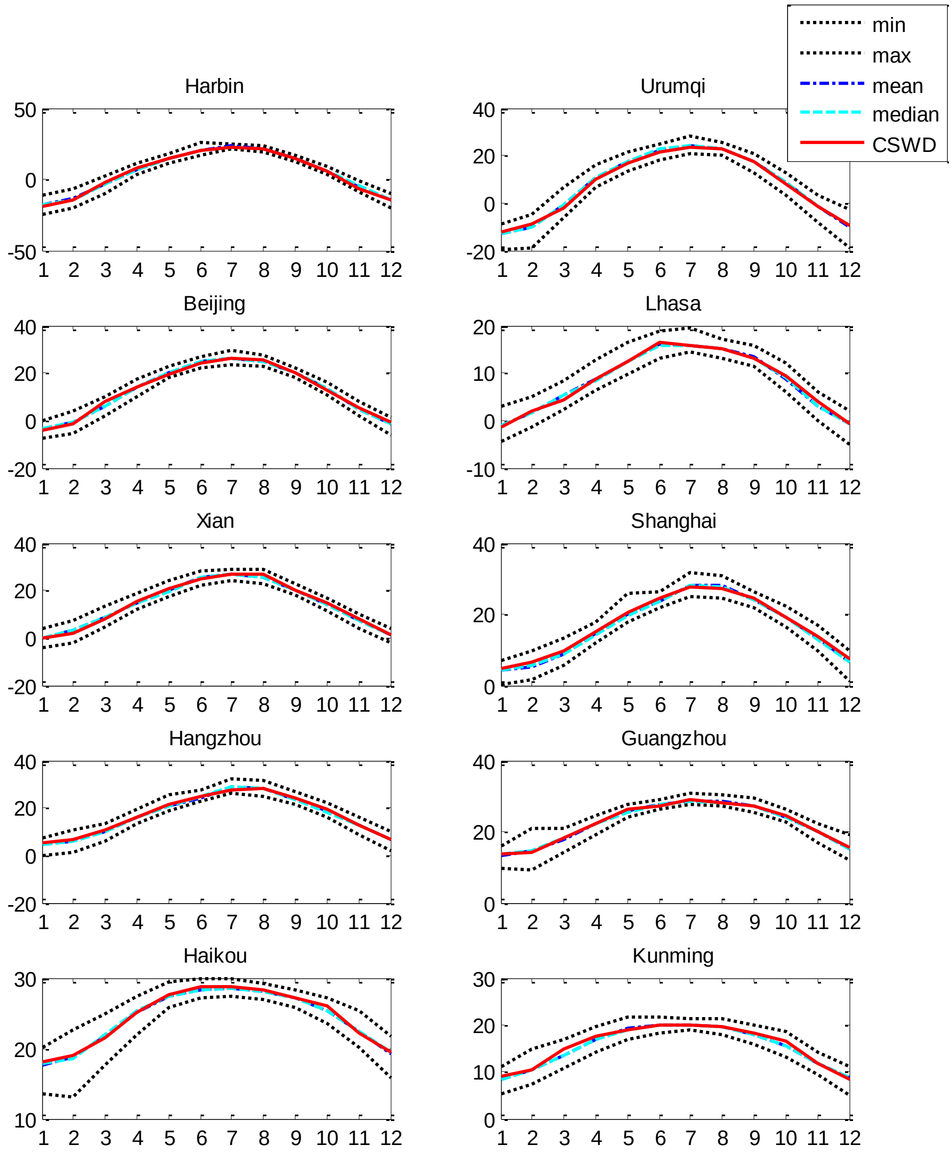

Fig. 3. Monthly average outdoor air temperature (°C) in the 10 cities

Notes: In each figure, the external black square dotted lines are the multiyear maximum and minimum of each month. The blue dashed dotted line is the multiyear average and the cyan-blue dashed line is the median.

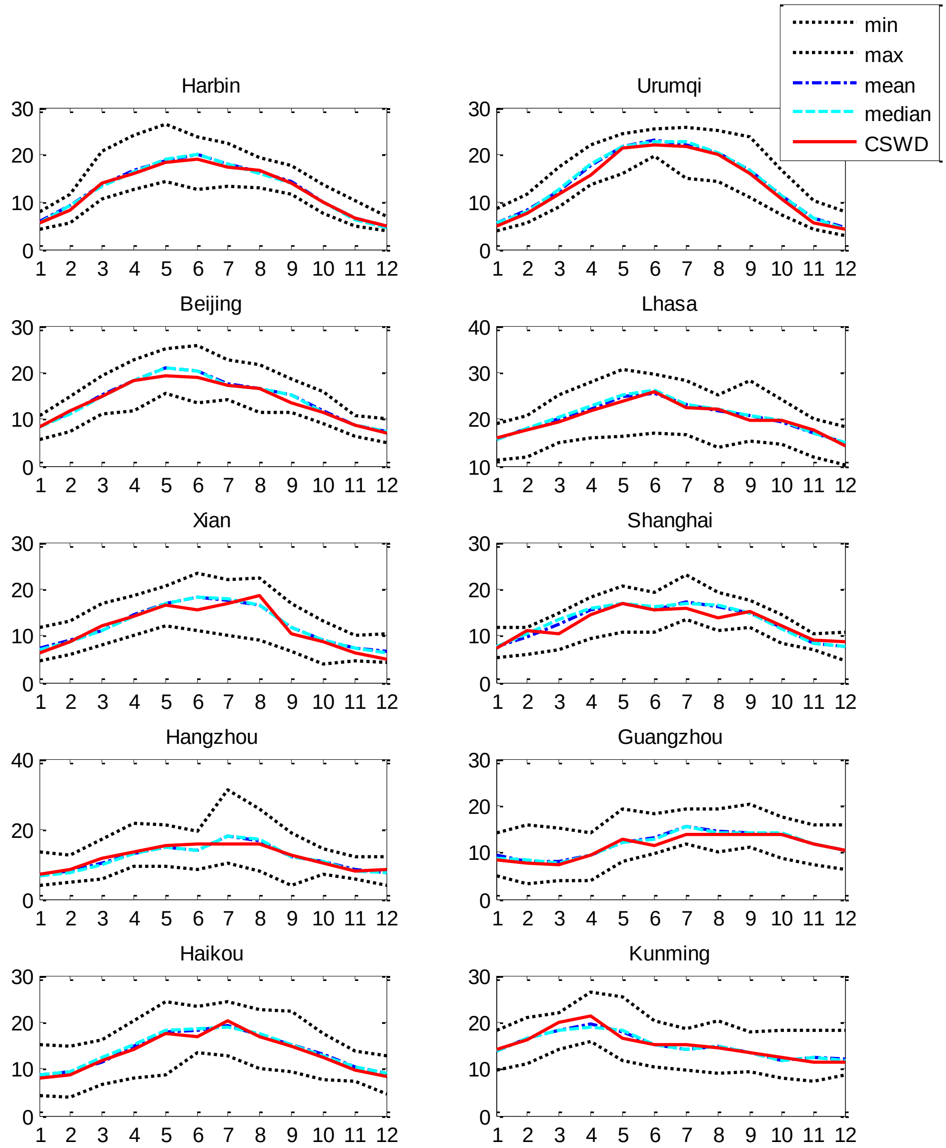

Fig. 4. Monthly average global horizontal radiation (MJ/m^2) in the 10 cities

Notes: In each figure, the external black square dotted lines are the multiyear maximum and minimum of each month. The blue dashed dotted line is the multiyear average and the cyan-blue dashed line is the median.

3.1.3. Heating degree days and cooling degree days

To provide a comprehensive look at the variation in the actual weather data, the annual heating degree days based on 18 °C (HDD18) and cooling degree days based on 26 °C (CDD26) are presented in Fig. 5. This figure shows that there was large year-to-year variation in the HDD18 and CDD26 results. The cold climate cities such as Harbin, Urumqi, and Lhasa had a difference in the annual HDD18 of more than 1000 during the 55-year period. The annual CDD26 of each city also differed greatly from year to year, especially in the warm climate cities such as Haikou and Guangzhou. In general, the heating-dominant cities displayed significant variation in terms of the HDD18, whereas the cooling-dominant cities displayed significant variation in terms of the CDD26.

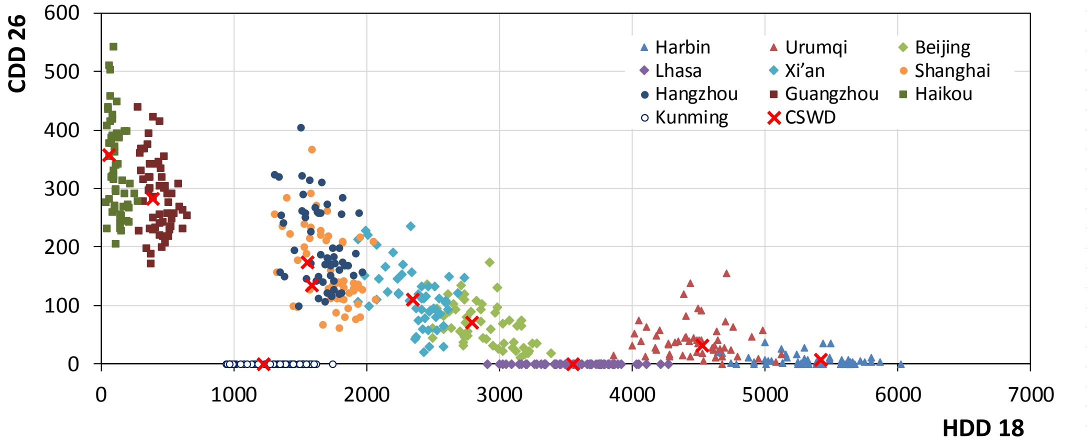

Fig. 5. Variations in the annual heating degree days (HDD18) and cooling degree days (CDD26) in the 10 cities

Notes: Each dot on the figure represented HDD18 or CDD26 for one specific calendar year, and each of the 10 cities was classified using a different color. The HDD18 and CDD26 of the typical year for each city are marked as a red cross.

Boxplots of the distributions of HDD18 and CDD26 across the climate zones are displayed in Fig. 6 and Fig. 7, respectively. The results show that the HDD18 results calculated by using the typical year file were closer to the long-term means for the cities in the SCZ and CZ. In the warm climate cities, especially in the HSCWZ, the HDD18 results of the typical year were equal to the first quartile Q1 for all the annual HDD18 results. Regarding the results for HDD18, the largest discrepancy between the mean and CSDW derived results was found in the HSCWZ.

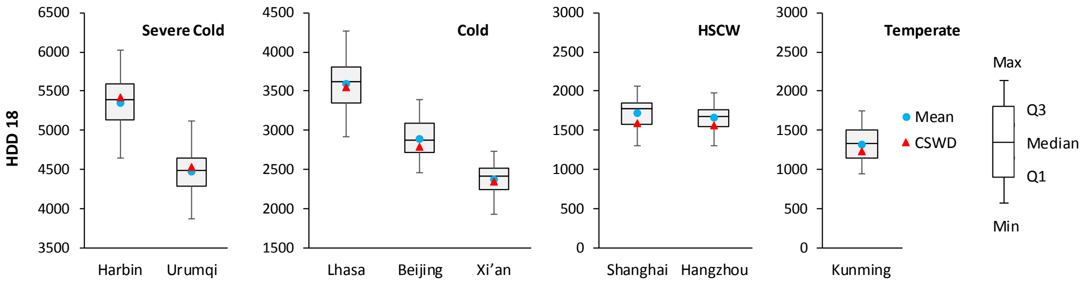

Fig. 6. Distribution of HDD18 in 8 of the 10 cities studied

Notes: The cities in the HSWWZ are not included in this figure because of the rather small number of HDD18 data points with low heating demand in this zone.

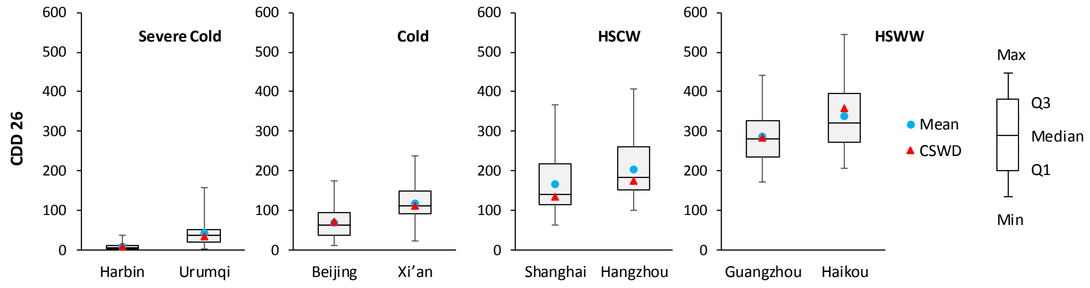

Fig. 7. Distribution of CDD26 in 8 of the 10 cities studied

Notes: Lhasa (CZ) and Kunming (TZ) are not included in this figure because of the rather small number of CDD26 data points with no cooling demand in these cities.

3.2. Building energy consumption

In this section, the impact of weather variation on building energy use was investigated. The heating load, cooling load, and total electricity use intensity (EUI) of the HVAC systems were calculated for the analysis, and the statistical results are listed in Table 5, Table 6, and Table 7, respectively. The variation ranges for the annual heating load, cooling load, and electricity HVAC EUI varied from 17.0 kWh/m^2 to 47.3 kWh/m^2, from 19.5 kWh/m^2 to 40.2 kWh/m^2, and from 7.4 kWh/m^2 to 21.6 kWh/m^2, respectively. The balance of the heating load and cooling load reduced the variation range of the total EUI of the HVAC systems to some extent. With respect to the representation of the typical year in terms of the building energy use, the typical year simulation results showed a large discrepancy compared to the multiyear simulation results. The total heating load simulated with the typical year file overestimated the multiyear results by up to 4.8%, and underestimation up to 12.7% also occurred. The biggest overestimates occurred in Harbin, whereas the biggest underestimates occurred in Hangzhou followed by Shanghai. For the cooling load, the typical year results sometimes overestimated the long-term mean energy use by as much as 17.8%. Kunming and Xi'an had the two biggest overestimates for the cooling load, which amounted to 17.8% and 16.6%, respectively. Harbin had the largest underestimate at 11.3%. Considering the total energy use, the typical year results overestimated the multiyear results by as much as 6.5% in Xi'an, whereas the typical year results underestimated the multiyear results by 7.9% in Shanghai.

Table 5. Statistics for the annual total heating load in 8 of the 10 studied cities

	Max (kWh/m^2)	Min (kWh/m^2)	Mean (kWh/m^2)	Range (kWh/m^2)	STD (kWh/m^2)	CSWD (kWh/m^2)	Variation CSWD-Mean (kWh/m^2)	Variation (% of the mean)
Harbin	122.2	87.7	104.5	34.5	8.8	109.5	5.0	4.8
Urumqi	111.0	63.7	87.5	47.3	8.4	91.5	3.9	4.5
Beijing	56.2	34.0	45.9	22.3	4.8	42.8	-3.0	-6.6
Lhasa	26.9	11.7	17.5	15.2	3.5	17.0	-0.6	-3.2
Xi'an	62.4	28.0	40.9	34.4	7.6	40.0	-0.9	-2.2
Shanghai	34.1	17.1	26.5	17.0	3.7	23.3	-3.2	-11.9
Hangzhou	38.7	18.8	28.5	19.8	4.7	24.9	-3.6	-12.7
Kunming	24.3	5.5	13.2	18.8	4.4	12.3	-0.9	-6.6

Notes: The statistical results of Guangzhou and Haikou are not shown in this table because of their rather low heating demand.

Table 6. Statistics for the annual total cooling load in the 10 cities

	Max (kWh/m^2)	Min (kWh/m^2)	Mean (kWh/m^2)	Range (kWh/m^2)	STD (kWh/m^2)	CSWD (kWh/m^2)	Variation CSWD-Mean (kWh/m^2)	Variation (% of the mean)
Harbin	47.8	28.3	36.3	19.5	5.0	32.2	-4.1	-11.3
Urumqi	57.9	30.5	42.2	27.3	6.1	39.1	-3.1	-7.3
Beijing	67.4	46.4	58.0	21.0	4.9	57.8	-0.2	-0.3
Lhasa	30.5	7.1	18.3	23.4	4.5	17.6	-0.7	-3.7
Xi'an	62.8	22.6	49.3	40.2	10.3	57.5	8.2	16.6
Shanghai	91.2	64.9	77.4	26.3	6.3	72.5	-4.9	-6.3
Hangzhou	94.1	61.4	74.7	32.6	7.4	75.7	1.1	1.4
Guangzhou	123.2	97.3	111.8	25.9	5.3	111.8	0.0	0.0
Haikou	172.9	120.9	144.6	52.0	11.9	148.3	3.7	2.5
Kunming	25.8	5.5	14.9	20.3	4.9	17.6	2.7	17.8

Table 7. Statistics for the annual total HVAC EUI in the 10 cities

	Max (kWh/m^2)	Min (kWh/m^2)	Mean (kWh/m^2)	Range (kWh/m^2)	STD (kWh/m^2)	CSWD (kWh/m^2)	Variation CSWD-Mean (kWh/m^2)	Variation (% of the mean)
Harbin	84.1	64.1	74.0	20.0	4.9	75.2	1.2	1.6
Urumqi	76.6	55.0	66.7	21.6	4.6	67.7	1.0	1.5
Beijing	55.3	39.7	49.3	15.6	3.0	47.5	-1.8	-3.6
Lhasa	21.8	14.4	17.3	7.4	1.5	16.7	-0.6	-3.4
Xi'an	48.7	37.7	42.9	11.1	2.7	45.7	2.8	6.5
Shanghai	48.7	35.6	43.0	13.1	2.9	39.6	-3.4	-7.9
Hangzhou	48.3	37.1	42.8	11.2	3.1	41.6	-1.2	-2.9
Guangzhou	52.0	40.7	47.0	11.3	2.4	46.2	-0.9	-1.9
Haikou	69.3	48.5	58.2	20.8	4.6	59.4	1.2	2.1
Kunming	16.4	8.0	11.9	8.4	1.7	12.6	0.7	5.6

The yearly variations in heating load and cooling load from 1960 to 2014 are shown in Fig. 8. In some cities such as Beijing, Guangzhou, and Haikou, the yearly heating and cooling loads mostly varied from the typical year by less than 20%, whereas in Kunming, the yearly differences were up to 100%.

There was no such change trend for differences in the multiyear simulation results. The differences were smaller during the early years in Harbin and Xi'an, and the differences were smaller in recent years in Urumqi. Thus, it is recommended that a rather long period be chosen when assessing long-term building performance.

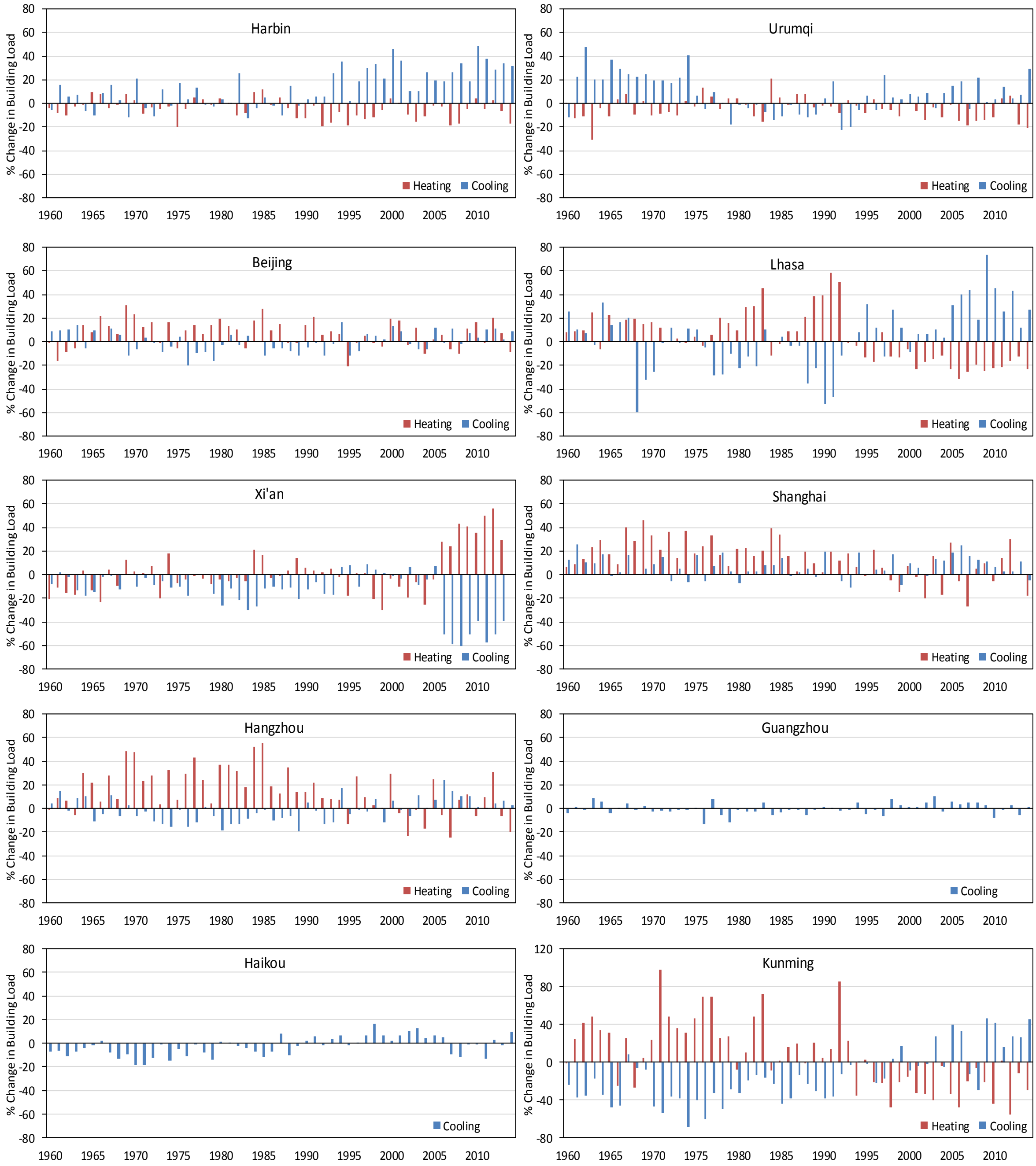

Fig. 8. Yearly variation in the heating and cooling loads in the 10 cities

Notes: The *y*-axis is the percentage change in the annual heating or cooling loads when compared to the typical year results. The *x*-axis is the time series of the long-term actual weather data. The variation percentages of the heating load in the HSWWZ are not displayed because the low amount of heating demand would have resulted in an abnormally large amount of variation, though the absolute variation value between a particular year and the typical year was small.

The relative and absolute changes in the total HVAC energy use in the 10 cities across the various climate zones are shown in Fig. 9. To obtain a quantitative understanding of the discrepancies, the number of years where the simulated results for the actual year were larger or smaller than those for the typical year was also counted (see Fig. 10). Specifically, Fig. 9 shows the variation range of the multiyear results in comparison with those for the typical year, while Fig. 10 indicates whether the typical year results overestimated or underestimated the actual energy use level. As shown in Fig. 9, the relative and absolute variations differed from city to city. Kunming had the largest percentage change, which ranged from -36.3% to 30.3%, whereas the absolute variation was not very large. This was because the total energy use in Kunming was relatively low compared to the other cities. In Shanghai, most of the years (49 out of 50 years) were associated with larger energy use than the typical year results. In Xi'an, however, most of the years (46 out of 50 years) were smaller than the typical year results. This was mainly because the same criterion was used to compile the typical year among all the cities. However, there was a chance that the sensitive weather parameters were different in each city, so the weighting of the weather parameters in each city when selecting the typical year should be different. Because the current method uses the same weightings regardless of building type, the local climatic characteristics may not necessarily be appropriate for all the cities across all the climate zones in China.

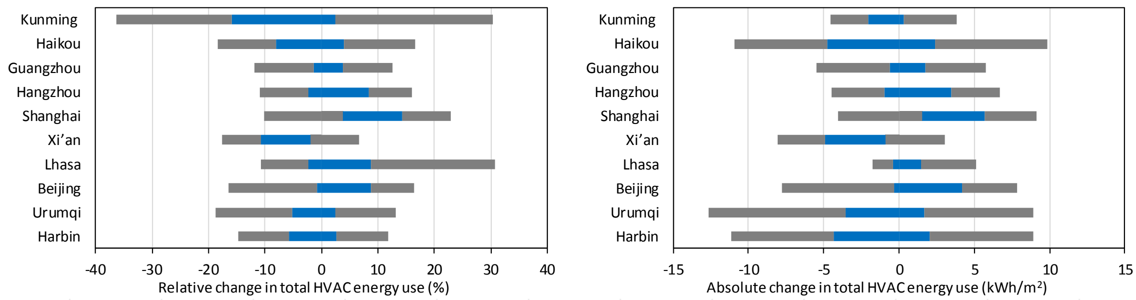

Fig. 9. Relative and absolute change in the total HVAC energy use in the 10 cities

Notes: The bars in the figure represent the difference in annual energy use compared to the results predicted by the typical year. In other words, the typical year simulation results for an individual city are regarded as the baseline and the 0 value refers to the typical year. The blue bar represents Q1–Q3. Thus, the blue and gray parts each contain half of the year.

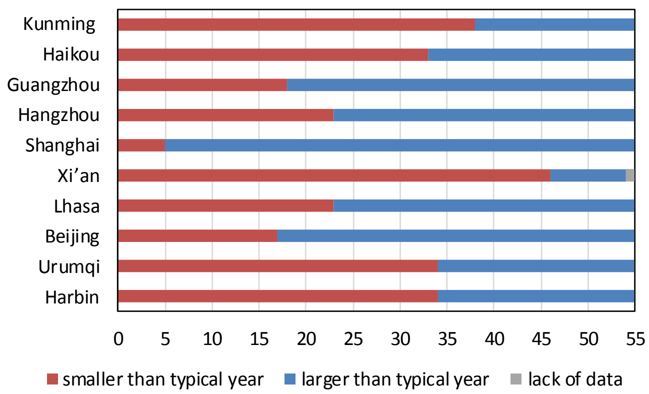

Fig. 10. Comparison between the multiyear and typical year results for the total HVAC energy use

3.3. *Building peak load*

The statistics for the annual heating peak load and cooling peak load are listed in Table 8 and Table 9, respectively. Compared with the long-term average annual peak load, the heating peak load of the typical year varied from -7.9% to 12.4%, whereas the cooling peak load varied from -9.7% to 12.4% among the cities. The differences were large between the typical year results and the long-term extreme maximum peak load. Regarding the heating peak load, the most significant variation amounted to -35.9% in Lhasa, followed by Urumqi at -24.0% and Kunming at -23.5%. The typical year results for Beijing were quite close to the long-term maximum, with a slight variation of -0.9%. Regarding the cooling peak load, Lhasa had the largest variation of -47.1% compared to the long-term maximum, and this was followed by Urumqi at -35.4% and Shanghai at -21.9%. In summary, the typical year peak load was lower than that for the long-term extreme conditions in the 10 cities. Hence, there could be risks involved with underestimating the electricity peak loads in any case if the typical year results are adopted when designing HVAC systems.

Table 8. Statistics for the annual heating peak load in 8 of the 10 cities

	Max (W/m^2)	Min (W/m^2)	Mean (W/m^2)	Range (W/m^2)	STD (W/m^2)	CSWD (W/m^2)	CSWD-Mean (W/m^2)	(CSWD-Mean)/Mean (%)	CSWD-Max (W/m^2)	(CSWD-Max)/Max (%)
Harbin	346.1	216.8	276.9	129.3	26.2	284.9	8.0	2.9	-61.1	-17.7
Urumqi	314.5	202.0	247.5	112.5	23.5	239.0	-8.5	-3.5	-75.5	-24.0
Beijing	182.9	132.0	163.9	50.9	12.2	181.2	17.3	10.6	-1.6	-0.9
Lhasa	124.2	63.4	83.9	60.8	14.8	79.6	-4.4	-5.2	-44.6	-35.9
Xi’an	181.2	122.1	149.9	59.1	13.3	152.8	2.9	1.9	-28.4	-15.7
Shanghai	155.4	107.2	126.5	48.1	10.6	116.5	-10.0	-7.9	-38.9	-25.0
Hangzhou	163.6	93.7	133.0	69.9	14.2	129.5	-3.5	-2.6	-34.1	-20.8
Kunming	153.5	61.4	104.5	92.1	21.8	117.5	12.9	12.4	-36.0	-23.5

Notes: The statistical results for Guangzhou and Haikou are not shown in this table because of their rather low heating demand.

Table 9. Statistics for the annual cooling peak load in the 10 cities

	Max (W/m^2)	Min (W/m^2)	Mean (W/m^2)	Range (W/m^2)	STD (W/m^2)	CSWD (W/m^2)	CSWD-Mean (W/m^2)	(CSWD-Mean)/Mean (%)	CSWD-Max (W/m^2)	(CSWD-Max)/Max (%)
Harbin	119.1	70.0	92.8	49.1	11.1	93.3	0.5	0.5	-25.8	-21.7
Urumqi	138.9	69.3	86.7	69.6	11.8	89.7	3.0	3.5	-49.2	-35.4
Beijing	133.4	87.9	112.7	45.4	10.4	126.7	14.0	12.4	-6.7	-5.0
Lhasa	67.6	30.4	39.4	37.2	6.8	35.8	-3.6	-9.1	-31.8	-47.1
Xi’an	131.1	68.9	111.3	62.1	14.0	118.4	7.2	6.4	-12.7	-9.7
Shanghai	162.3	116.9	137.6	45.3	9.1	126.7	-10.9	-7.9	-35.6	-21.9
Hangzhou	149.0	114.6	133.3	34.4	7.4	129.3	-4.0	-3.0	-19.6	-13.2
Guangzhou	141.4	110.7	124.0	30.6	6.4	129.7	5.8	4.6	-11.6	-8.2
Haikou	143.1	109.5	122.2	33.6	7.1	137.2	15.0	12.3	-5.9	-4.1
Kunming	54.8	36.6	45.1	18.3	4.2	48.6	3.6	8.0	-6.2	-11.3

Similar to the analysis on energy use, the yearly change distributions and contrast statistics for heating and cooling peak loads are shown in Fig. 11, Fig. 12, and Fig. 13. In terms of the heating peak load, the typical year results underestimated the actual heating peak loads for Shanghai in most years (49 out of 50 years). For Beijing and Kunming, the typical year results overestimated the heating peak loads in the majority of years (in 50 and 40 years, respectively). Regarding the cooling peak load, the typical year results were larger than 75% of the years for Haikou, Beijing, and Guangzhou. This was especially apparent in Haikou, where only one year between 1960 and 2014 had a cooling peak load larger than that for the typical year. In other words, the typical year results overestimated the cooling peak loads for these cities. On the other hand, the cooling peak load, in general, was underestimated for Shanghai and Hangzhou; the typical year results for these cities were smaller than the actual year results for 49 and 38 years, respectively. The variations differed from city to city. The variation inherent in the weather influenced the peak demand more significantly than energy use did, which makes sense, as the peak is one single maximum value that occurs at a single time, whereas energy use is an aggregate of values across all days of a year.

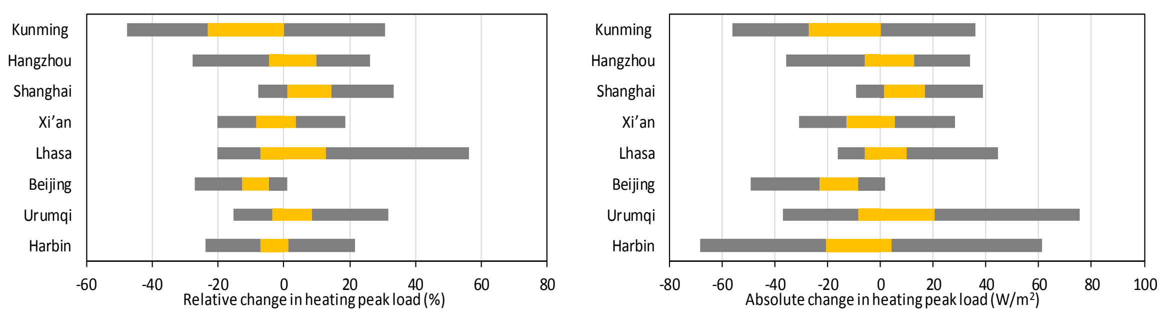

Fig. 11. Relative and absolute change in the heating peak loads in 8 of the 10 cities

Notes: The cities in the HSWWZ are not included in this figure because of the rather small amount of heating peak load given the low heating demand in this zone.

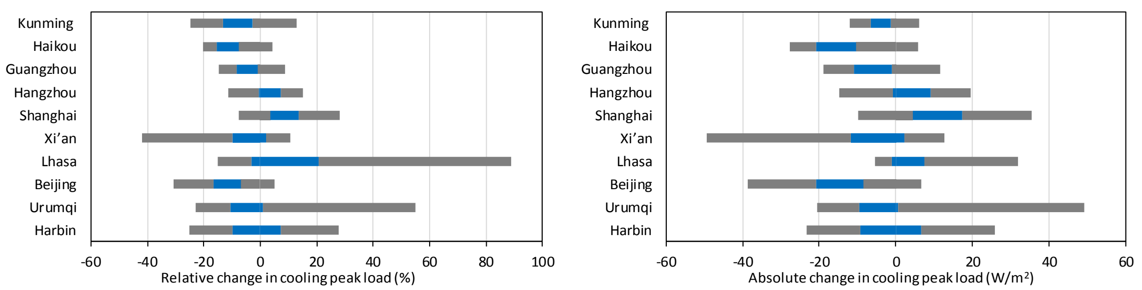

Fig. 12. Relative and absolute change in the cooling peak load for the 10 cities

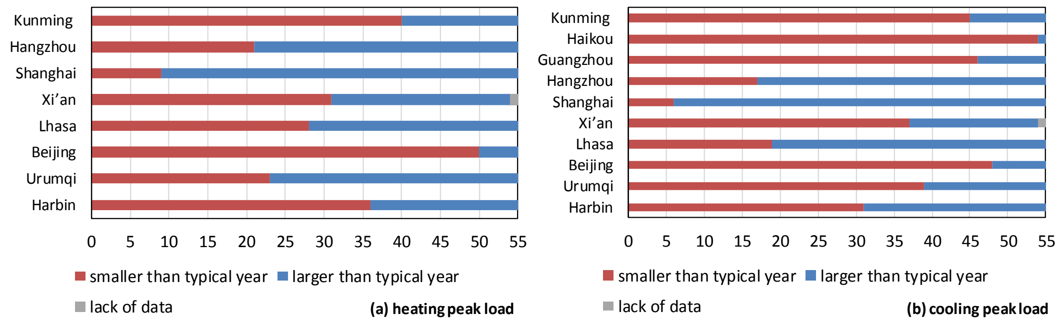

Fig. 13. Comparison between the multiyear and typical year results for the (a) heating peak load and (b) cooling peak load

Notes: The cities in the HSWWZ are not included in this figure because of the rather small amount of heating peak load in this climate zone.

4. Discussion

Through the previous analysis, it was proven that although a typical year can be used to represent the long-term average weather conditions during building energy performance assessments, there are problems associated with this method. First, in accordance with climate change, the weather conditions may vary significantly from year to year. The typical year, as a single and artificial year, is thus unable to reflect the variation range of the actual climate given the present changing conditions. As a result, the energy use estimated over a long-term period can differ greatly from results derived by using the typical year approach. In the current study, this discrepancy sometimes reached up to 21.6 kWh/m^2. Second, because of limitations related to the representation of extreme weather conditions, the typical year is not appropriate for designing systems or sizing equipment under the worst-case scenario. For example, if we take the cooling peak load simulated by the typical year as the criterion to design an air-conditioning system, the capacity of the equipment will be insufficient in some years. This shortage could be up to 50 W/m^2, which might result in a poor quality indoor environment and occupant discomfort. Finally, because of the different climatic characteristics of different cities, the meteorological sensitivity could vary. For example, in solar energy-rich areas, the radiation intensity plays a vital role in the building energy consumption. The radiation thus should have the highest weight during derivation of the typical year. However, the typical year is currently selected with the same weights for weather parameters no matter the location or the building type. This usually causes the typical year to under-predict the energy use for a particular city, but over-estimate the energy use for another city.

In summary, typical year simulations will have serious limitations in some cases. One possible solution would be to adopt multiyear simulations. Multiyear simulations can solve the above problems and provide designers or engineers a comprehensive understanding of the building performance under various conditions. Nevertheless, there is a possibility that someone will want to determine the life-cycle building performance but be unwilling to do the multi-run simulations. Additionally, cases may occur where an actual weather database is not available. In such situations, multiyear simulations might not be a feasible option, though this approach is clearly advantageous compared with typical year simulations. In those cases, a simplified method to estimate the variation range of energy use during the life-cycle period, such as 55-years, can be used. Using the results of 10 cities, we obtained the relationship between the energy use for a typical year and the maximum/minimum of the total life-cycle period. The fit formulas and R^2 values are shown in Fig. 14. It can be seen that the maximum/minimum energy use can be well predicted by the typical year results. Namely, the variation range of energy use in the total life-cycle period can be estimated by the typical year simulations with this proposed simplified approach.

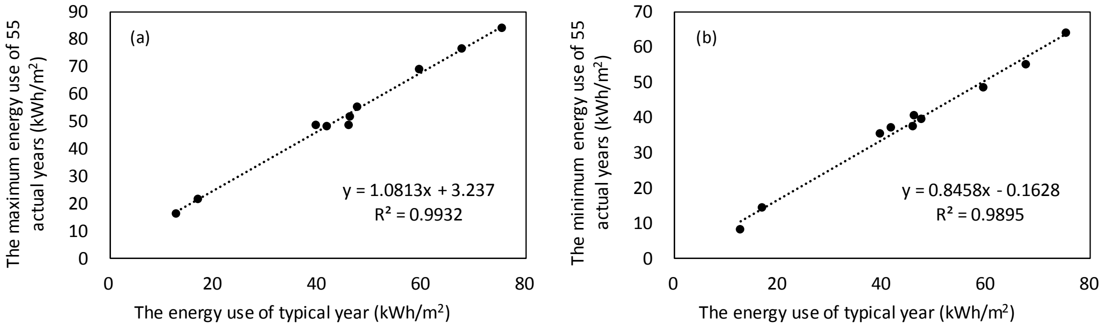

Fig. 14. The relationship between the energy use of a typical year and the (a) maximum and (b) minimum energy use according to the 55-year analysis results

5. Conclusions

In this study, a typical year data file and a 55-year actual meteorological year database were compiled for 10 cities covering all the climate zones in China. The representativeness of the typical year was assessed by studying the statistics as well as the monthly profiles of the weather data compared to the long-term weather data. By setting up a prototype office building in the DeST program, the differences in energy use and peak load between the typical year and actual years were also analyzed.

The major contributions of this study cover three aspects. (1) To the best of our knowledge, it is the first paper to evaluate the typical year simulations with as much as 55 years of actual weather data. The life cycle of most buildings is over 50 years, and hence, such long-term analyses are important. (2) This paper compares and analyzes the differences between typical year simulations and multiyear simulations not only in terms of the weather parameters, but also in terms of the energy impacts due to climate change. While most previous studies focused on the question of whether the typical year can represent the long-term means, this paper provides additional insights into new multiyear simulations and their advantages. (3) A simple and fast estimation method for the variation range in energy use is discussed for those who do not want to run so many simulations or are unable to access an actual weather database.

The main findings of the study are as follows:

1) The weather data varied significantly from year to year. The variation was more significant in the heating-dominant regions including the SCZ and the CZ in China;
2) The typical year provided a good representation of the weather variables in regard to long-term means, but it could not reflect the variation range in the weather data;
3) The HDD18 and CDD26 calculated by use of the typical year did not necessarily represent the long-term means, especially in the HSCWZ in China;
4) The typical year simulations tended to overestimate or underestimate the energy use and peak load. The representativeness of each city differed greatly; and
5) The variation in weather influenced the peak load more significantly than energy use.

These findings imply that Chinese policy makers and building designers should design systems or buildings that are more adaptable to climate change in cold climate areas because of the significant variation of weather. Furthermore, HDD18 and CDD26 in the current building design standard are generally calculated based on the typical year; yet, the question remains to be answered whether these values are suitable for estimating the future potential energy consumption.

There is no doubt that typical year simulations can reduce the computational work and save time, but because of the limitations inherent in the generation methods of the typical year weather data, there are many deficiencies associated with single year simulations. With the increase in computational power of personal computers and meteorological technology, it has become possible to use a multiyear actual weather database instead of an artificial single year to assess long-term building performance. The multiyear simulation method addresses the problems associated with the use of a typical year. Not only the variation, but also the extreme conditions caused by weather changes can be reflected fully in the multiyear simulation results. Thus, it is time to rethink the use of a typical year and gradually adopt multiyear weather data in building performance simulations.

Because of the effort required in collecting original weather data, the current paper focused only on Chinese cities, and the paper proved that the adoption of multiyear simulations can help to improve building performance assessments in China. Similar conclusions could likely be drawn in other countries with similar climate conditions. To gain international and comprehensive insight, the authors wish to cooperate with scholars from other countries in future work to determine whether the application of multiyear simulations is proper in various climates.

Acknowledgments

This work is funded by the Engineering and Physical Sciences Research Council (EPSRC) grant (EP/N009703/1) and the National Natural Science Foundation of China (NSFC) grant (51561135001). This work was also supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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